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RESEARCH ARTICLE

Use of artificial landscapes to isolate controls on burn probability

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Abstract Techniques for modeling burn probability (BP) combine the stochastic components of fire regimes (ignitions and weather) with sophisticated fire growth algorithms to produce high-resolution spatial estimates of the relative likelihood of burning. Despite the numerous investigations of fire patterns from either observed or simulated sources, the specific influence of environmental factors on BP patterns is not well understood. This study examined the relative effects of ignitions, fuels, and weather on mean BP and spatial patterns in BP (i.e., BP variability) using highly simplified artificial landscapes and wildfire simulation methods. Our results showed that a limited set of inputs yielded a wide range of responses in the mean and spatial patterning of BP. The input factors contributed unequally to mean BP and to BP variability: so-called top-down controls (weather) primarily influenced mean BP, whereas bottom-up influences (ignitions and fuels) were mainly responsible for the spatial patterns of BP. However, confounding effects and interactions among factors suggest that fully separating top-down and bottom-up controls may be impossible. Furthermore, interactions among input variables produced unanticipated but explainable BP patterns, hinting at complex topological dependencies among the main determinants of fire spread and the resulting BP. The results will improve our understanding of the spatial ecology of fire regimes and help in the interpretation of patterns of fire likelihood on real landscapes as part of future wildfire risk assessments.

Keywords Burn probability · Burn-P3 simulation model · Ignitions · Fuels · Fire weather

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Introduction

Fire is a natural ecosystem process affecting landscapes worldwide (Bond and van Wilgen 1996;

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Krawchuk et al. 2009) and an integral part of one of the most important pattern-process feedbacks on natural landscapes (Turner et al. 1989; Peterson 2002). Although fire regimes have been described for many areas of the globe (e.g., Niklasson and Granström 2000; Rollins et al. 2002; Russell-Smith et al. 2003), we are only beginning to develop a mechanistic understanding of how biophysical and anthropogenic factors affect the spatio-temporal distribution of fires. Because an understanding of where and when fires occur is necessary for our successful coexistence with fire, either "wild" or prescribed, land managers have developed numerous tools for assessing the spatially-explicit likelihood of fire—also known as burn probability (BP)—in a risk analysis framework (Miller 2003; Ager et al. 2006; Finney 2006).

Fires require the co-occurrence in time and space of three main factors: fire-conducive weather, ignitions, and flammable vegetation (i.e., fuels) (Moritz et al. 2005; Parisien and Moritz 2009). Weather has often been called a 'top-down' control on fire behavior because of its mesoscale impact, whereas ignitions and fuels are considered 'bottom-up' (Heyerdahl et al. 2001). Weather affects the occurrence, size, and shape of fires through the frequency of consecutive days of fire-conducive weather, the severity of fire weather conditions, and the constancy of wind direction (Moritz 1997; Beverly and Martell 2005). Ignitions are seldom random on the landscape (Krawchuk et al. 2006). High ignition densities, which tend to be near urban areas and roads, may translate into high concentrations of fires (Parisien et al. 2004; Badia-Perpinyà and Pallares-Barbera 2006), but not necessarily the greatest area burned (Sturtevant and Cleland 2007; Syphard et al. 2007). Fuels affect the spread of fires according to the relative proportions of fuel types on the landscape (Finney 2003; Leohle 2004) and their spatial configuration (Finney 2001; Parisien et al. 2007).

Although ignitions, fuels, and fire-conducive weather are necessary ingredients for fire, their respective influence on the manifestation of fire patterns appears to vary enormously among landscapes, as well as across temporal and spatial scales (Falk et al. 2007). Fire ignition and spread respond sequentially to a complex suite of environmental factors (including weather variables) that vary in both time and space. The complexity of fire-environment relationships thus makes it intrinsically difficult to disentangle the relative influence of these factors, especially on landscapes where topography acts as a modifier (Taylor and Skinner 2003; van Wagtendonk and Cayan 2008). Moreover, determining the relative influence of environmental factors can be further complicated by a certain dichotomy between so-called "normal" and "extreme" fire-conducive conditions. For example, in some environments (e.g., Mediterranean), the influence of fuel type on fire spread is greatly diminished under extreme weather conditions (Moritz 2003; Nunes et al. 2005).

We hypothesize that there are basic relationships between BP and its environmental controls that hold for most, if not all, fire-prone landscapes (Fig. 1), and that the relative strengths of these relationships can be expected to vary among environmental contexts. A distinction needs to be made between the mean landscape BP and the spatial variability in BP. For example, the number of ignitions, the flammability of the fuels, and the mean duration of fire-conducive weather positively influence mean landscape BP, but affect the spatial variability in BP differently (Fig. 1). Furthermore, interactions among factors are likely to affect BP (Yang et al. 2008), potentially confounding perceptions of which factor is most important.

Computer simulation models that explicitly ignite and spread fires across a landscape provide an opportunity for significant advancement in our understanding of the factors driving fire likelihood, because variables can be controlled and fire occurrence patterns can be more easily interpreted. We used a spatially explicit simulation model to investigate the relative influence of key environmental factors on BP. We designed heuristic artificial landscapes and three simulation experiments focusing on how ignitions, fuels, and weather influence mean BP and BP variability. We developed scenarios to crudely represent archetypal fire regimes from around the globe and to discern the influences of so-called top-down (weather) and bottom-up (fuels and ignitions). A factorial design allowed us to reveal effects of interactions among factors. In an effort to simplify our experimental design, we did not consider topography in this study. Although topography can influence spatio-temporal patterns of fires (Rollins et al. 2002; Stambaugh and Guyette 2008), it does so indirectly, by influencing ignition and fuel patterns, as well as weather conditions (wind vectoring).

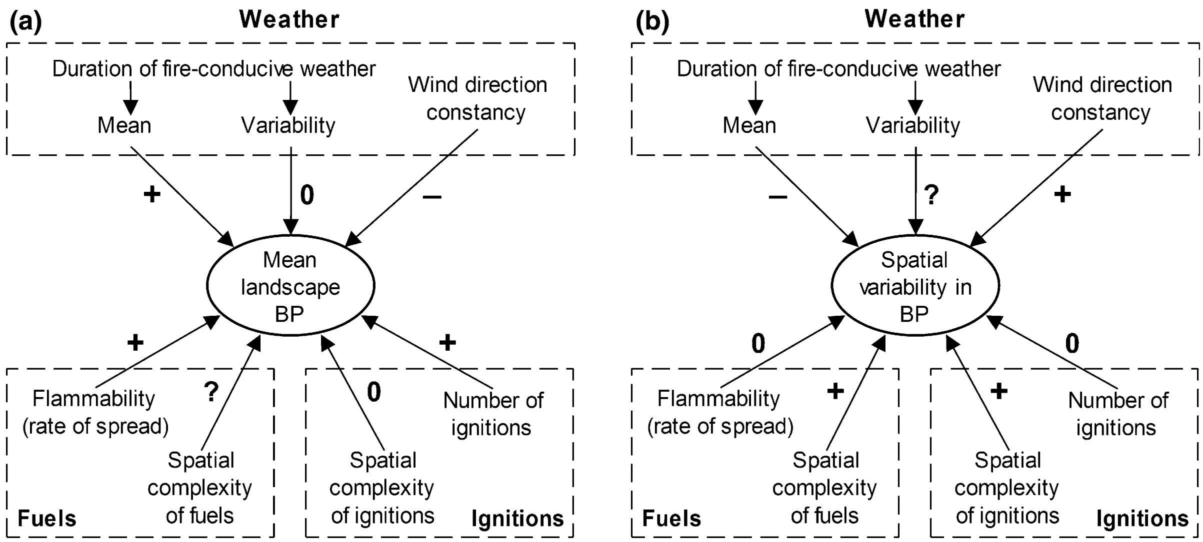

Fig. 1 General expectation of the effect of some components of weather, fuels, and ignitions on the **a** mean landscape-level burn probability (BP) and the **b** spatial variability in BP patterns. The *symbols* associated with each *arrow* indicate the following: '+' is an increase, '–' is a decrease, '0' means no net change, and '?' is used when factors could yield either an increase or decrease

Methods

We used the Burn-P3 model (Parisien et al. 2005) to estimate BP for specific combinations of experimental factors ("simulation scenarios") across flat (slope = 0) 700 × 700-cell study landscapes. To avoid edge effects, a buffer at least as wide as the length of the frontal fetch of the largest simulated fire was added to the study landscapes. The effect of ignitions—both numbers and spatial patterns—was tested by using an experimental factor (IGNIT) with multiple levels (Table 1). The flammability and spatial arrangement of fuels was similarly tested with the FUELS factor. The effect of fire-conducive weather was tested with three experimental factors: mean fire size (SIZE), which is analogous to the mean duration of fire-conducive weather; fire size distribution (DIST), a measure of variability in the duration of fire-conducive weather; and the constancy of wind direction (DIR). The three weather-related factors are global inputs to the Burn-P3 model, that is, those applied uniformly to every point on the landscape. The IGNIT and FUELS factors are local, as they vary as a function of the location on the landscape.

The relative influence of each experimental factor on mean landscape BP (hereafter BP_{mean}) and BP variability (BP_{var}) was evaluated in three experiments (Table 2). The 'ignitions experiment' examined the influence of ignition patterns and the interactions of this factor with mean fire size and wind direction. The 'fuels experiment' examined the effect of fuel patterns and interactions with ignition patterns and mean fire size. The 'weather experiment' assessed the effect of wind direction constancy and fire size distribution on BP and interactions with fuel patterns. Computational constraints dictated that only the most informative levels of a given factor were used in some analyses (see sections below).

Burn-P3 simulation model

Burn-P3 simulates fire growth based on the physical factors that control fire spread and the larger-scale probabilistic components of fire regimes (e.g., ignitions and fire weather) on a landscape of known fuels and topography. The model simulates the ignition and spread of a very large number of fires on a rasterized landscape to calculate spatially explicit BP for each cell for a snapshot in time (e.g., year). It does not account for vegetation succession. Monte Carlo methods are used to draw the locations of ignitions from a probability density grid. A fire growth model (Tymstra et al. 2009) is then used to calculate fire spread through complex terrain and fuels, as

Table 1 Experimental factors in the three burn probability experiments

Factor	Description	Levels	Specifications
SIZE	Mean fire size	Large (Lg)	1/20 of study area
		Small (Sm)	1/100 of study area
DIST	Fire size distribution	Constant (Cst)	16 h of burning
		Regular (Reg)	8–24 h (mean = 16) of burning
		Negative exponential (Exp)	8–40 h (mean = 16) of burning
DIR	Direction of burning	South (S)	One direction; perpendicular to rectangular fuel feature
		West (W)	One direction; parallel to rectangular fuel feature
		Random (Rnd)	Eight directions
IGNIT	Spatial pattern of features of higher relative ignition density for two relative density levels	Uniform ignitions	All cells have equal likelihood of ignition
		Linear, high density (LinHi)	Ignitability ratio 10:1
		Clustered, high density (CluHi)	
		Linear, low density (LinLo)	Ignitability ratio 2:1
		Clustered, low density (CluLo)	
FUELS	Configuration and composition of spatial fuel features	Uniform fast-burning fuels	All cells have equal rate of spread
		Rectangular slow-fuel features; 25% slow fuel (Rec25)	Rate of spread for slow fuel is half that of fast fuel
		Circular slow-fuel features; 25% slow fuel (Cir25)	
		Rectangular fast-fuel features; 75% slow fuel (matrix) (Rec75)	
		Circular fast-fuel features; 75% slow fuel (matrix) (Cir75)	

described by the Canadian Fire Behavior Prediction (FBP) System (Forestry Canada Fire Danger Group 1992). Within the FBP System, flammable vegetation is categorized into fuel types, which are used to calculate quantitative fire behavior outputs for a given set of fire weather inputs. Fire weather conditions drive fire spread and the length of the fire-conducive burning period are modeled stochastically from user-supplied distributions. Although fire weather conditions may change hourly, here they were set as constant for 7- or 8-h periods, which would be analogous to a daily burning period.

In this study, the ignition and growth of one fire was simulated per iteration or model run. The cells burned by each fire were recorded as burned and the landscape was re-initiated after each fire (i.e., no interactions were allowed among fires). The areas burned were ultimately compiled in a cumulative grid of the number of times each cell burned. The final Burn-P3 product is a BP grid map where the BP of each cell i is calculated as:

$$\mathrm{BP}_i = \frac{b_i}{N} \times 100 \quad (1)$$

where b_i is the number of times that cell i burned, N is the number of fires simulated, and BP_i represents the percent probability of cell i being burned over the defined temporal extent. The model is inherently stochastic; therefore, a large number of fire simulations is required to produce a stable BP map under a given set of simulation inputs. We determined that, depending on the scenario, this number should range from 1×10^5 and 8×10^5 fires to restrict the relative BP difference among runs of the same scenario to less than 4%.

Inputs to the model

Ignitions

Ignitions in Burn-P3 are cell-based inputs, the probability of which were varied according to 3

Table 2 Characteristics of burn probability (BP) experiments

Experiment	Design	Factors and levels					Simulation scenarios
		SIZE	DIST	DIR	IGNIT	FUELS	
Ignitions	BP = IGNIT + SIZE + DIR	Sm	Cst	Rnd	Uniform	Uniform	20
		Lg		S	CluHi		
					LinHi		
					CluLo		
					LinLo		
Fuels	BP = SIZE + FUELS + IGNIT	Sm	Cst	S	Uniform	Uniform	30
		Lg			CluHi	Rec25	
					LinHi	Cir25	
						Rec75	
						Cir75	
Weather	BP = DIST + FUELS + DIR	Lg	Cst	S	Uniform	Uniform	27
			Reg	W		Rec25	
			Exp	Rnd		Cir25	

In the models, the dependent variable was either mean BP or BP variability

SIZE = fire size, where Sm = small and Lg = large; DIST = fire size distribution, where Cst = constant, Reg = regular and Exp = negative exponential; DIR = wind direction, where S = south, W = west and Rnd = random; IGNIT = ignition features, where CluHi = clustered high density, LinHi = linear high density, CluLo = clustered low density and LinLo = linear low density; FUELS = fuel type, where Rec25 = rectangular slow-fuel features with 25% slow fuel, Cir25 = circular slow-fuel features with 25% slow fuel, Rec75 = rectangular fast-fuel features with 75% slow fuel (in matrix) and Cir75 = circular fast-fuel features with 75% slow fuel (in matrix)

spatial configurations (random, clustered, and linear) and 2 ignitability ratios (high and low), which together constituted the five levels of the IGNIT factor (Table 1). The first level represented ignitions located randomly in space. The second level represented five large circular features in which individual cells were 10 times more likely to ignite than were cells in the surrounding matrix (clustered, high-density [CluHi]) (Fig. 2). The third level was similar to the second, but the features were two perpendicular lines (linear, high-density [LinHi]). The clustered and linear features were devised to approximate the effect of increased ignitions around towns and roads, respectively. The fourth and fifth levels had the same spatial features as the second and third levels, respectively, but the cells of the features were only twice as likely to ignite as those in the surrounding matrix (clustered, low-density [CluLo] and linear, low-density [LinLo]). In each case, the ignition features covered 10% of the study landscape.

Fuels

Fuels were also integrated as gridded inputs, whereby cells were classified as one of two fuel types, fast or slow, for which the rate-of-spread ratio was 2:1. To achieve this ratio, the fast fuel type was the FBP System's Boreal Spruce and the slow fuel type was a mix of coniferous and leafed-out deciduous (Boreal Mixedwood with a 45% coniferous component). The FUELS factor comprised five levels. The first level consisted of uniform fast fuels. The second level, Rec25, consisted of five rows of staggered rectangular features having a 2:1 ratio of length to width, laid out lengthwise in an east–west orientation (Fig. 2). The rectangular features represented slow fuels (accounting for 25% of the total area) embedded in a matrix of fast fuels (75%). The third level was the same as the second, but the features were circular (Cir25). The fourth and fifth levels (Rec75 and Cir75, respectively) had the same spatial configurations as the second and third levels, but the slow and fast fuels

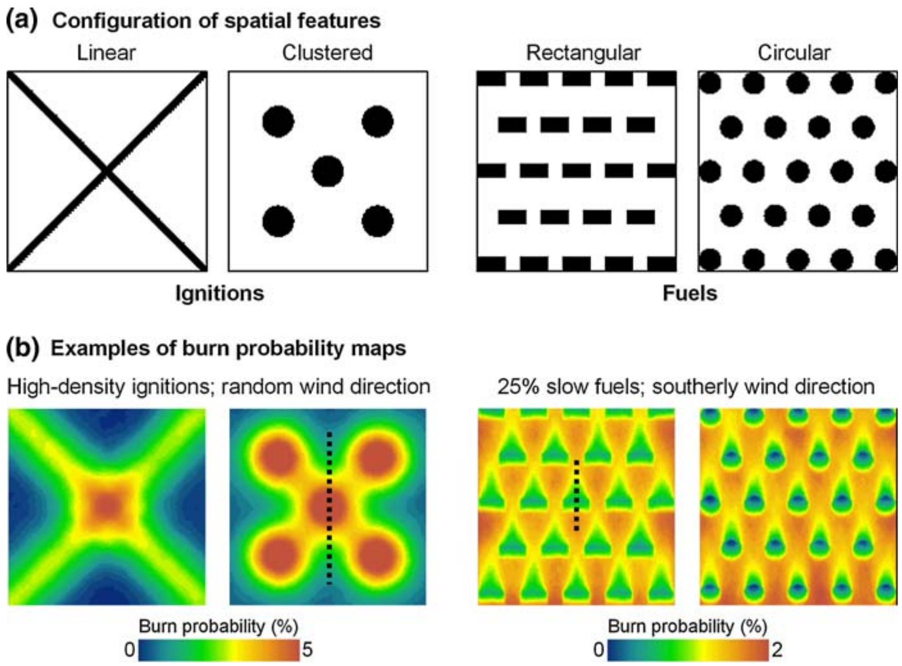

Fig. 2 The inhomogeneous fuel and ignition patterns used in the burn probability (BP) analysis (**a**) and examples of burn probability maps created using these inputs (**b**). Relative flammability and ignitability differ between the interior and exterior of spatial features (*black areas* in **a**) in the fuel and ignition grids, respectively. The *dashed lines* on the BP maps indicate the position of transects along which BP values were sampled in the analysis of local BP patterns (Fig. 4)

were inverted, with the features containing fast fuels (25%) embedded in a matrix of slow fuels (75%). The fuel features were designed to be analogous to distinct vegetation stands or fuel treatments across a landscape.

Weather

Fire weather conditions were selected to produce a range of fire sizes and shapes described by the factorial levels of the SIZE, DIST, and DIR experimental factors. In Burn-P3, fire weather is input as daily weather observations (temperature, relative humidity, wind speed, wind direction, and 24-h precipitation) at noon local standard time and the associated fuel moisture codes and fire behavior indexes from the Canadian Forest Fire Weather Index System (Van Wagner 1987). All of these variables except wind direction were held constant among simulation scenarios. A wind speed of 15 km/h was used to approximate a 2:1 length-to-breadth ratio for the perimeter of an elliptical fire. Different fire sizes were achieved by altering the duration of the burning period.

To assess the effect of the mean duration of fire-conducive weather, two levels were developed for the SIZE factor: small (Sm) and large (Lg), corresponding to fire sizes of 1/100 and 1/20 of the area of the study landscape, respectively (FUELS = Uniform) (Table 1). Under the specified weather conditions, these sizes represent 7 (Sm) and 16 h (Lg) of burning.

The variability in the duration of fire-conducive weather was evaluated using three fire size distributions having the same mean burning period (16 h) within the DIST factor. The constant (Cst) distribution produced fires that burned for 16-h periods (as for the Lg fires of the SIZE factor) with no variance. The regular (Reg) distribution produced fires with an equal likelihood of burning for 8-, 16- or 24-h periods. The negative exponential (Exp) distribution produced fires that burned for 8-, 16-, 24-, 32-, or 40-h periods, as described by the following decay function:

$$f(x) = e^{-\lambda x} \qquad (2)$$

where x is the duration of the burning period for each fire and $\lambda = 1/\bar{x}$, where $\bar{x}$ is the mean number of hours of burning. In the Exp distribution, most fires were smaller than those that used for the mean burning period, but the ones with a burning period longer than average were disproportionately large. Specifically, a 40-h burning period, which occurred in 5.8% of the runs, burned 37% of a landscape of uniform fuels.

The DIR factor was used to examine the effect of the constancy of wind direction on BP, as well as effect of the orientation relative to rectangular fuel features. Three levels were devised for the DIR factor: fires burning exclusively from the south (S), fires burning exclusively from the west (W), and fires burning from random directions (Rnd), where wind direction varies randomly among 8-h burning periods.

Analysis

Effects of combinations of inputs on BP_{mean} and BP_{var}

In order to facilitate comparison among simulation scenarios we evaluated the effects of the various combinations of inputs on $\mathrm{BP_{mean}}$ and $\mathrm{BP_{var}}$ as the relative departure of BP values from the mean BP (i.e., a single value) computed for scenarios using uniform IGN and FUELS inputs for each level of SIZE, DIR, and DIST. For example, in the ignitions experiment, all BP values for the scenarios created with each of the four nonrandom levels of IGNIT (CluHi, LinHi, CluLo and LinLo) were compared with the $\mathrm{BP_{mean}}$ of the scenario created with random ignitions (IGNIT = Uni) for each level of DIR (Rnd and S). The normalized BP difference from the uniform case, NBPD, was computed as:

$$\mathrm{NBPD}_{ijk} = \left(\mathrm{BP}_{ijk} - \sum_{i=1}^{n} \frac{\mathrm{BP}(u)_{ijk}}{n}\right) \times 100 \qquad (3)$$

where BP_{ijk} is the BP value for cell i for a given factor j and level k, and the summation term represents the $\mathrm{BP_{mean}}$ of the study landscape simulation produced with uniform values (u) of all grid cells (n) for factor j and level k. The mean NBPD ($\mathrm{NBPD_{mean}}$) and standard deviation of NBPD ($\mathrm{NBPD_{std}}$) were plotted for each scenario in each experiment. In addition, values for $\mathrm{NBPD_{mean}}$ were computed within fuel and ignition features to provide a coarse measure of the influence of that particular feature on BP.

Relative importance of environmental factors

The relative importance of the factors affecting $\mathrm{BP_{mean}}$ and in $\mathrm{BP_{var}}$, as well as their second-order interactions, was assessed for each experiment using generalized linear models (GLM). The experimental factors were treated as independent categorical predictor variables with multiple levels (Table 2). The contribution of each factor and their interactions was determined by leaving the term of interest out of the model and calculating to what extent this omission reduced model performance in comparison with the full model. To enable computation and to limit spatial autocorrelation in the model, a subset of cells was systematically sampled from the BP maps at equal intervals. Heuristic explorations showed that a grid of 36 × 36 points (total 1296 points; distance of 20 cells between samples) provided a good compromise between depicting the spatial BP patterns of interest and minimizing spatial autocorrelation with a fairly low number of points relative to a random sampling scheme.

The contribution to $\mathrm{BP_{mean}}$ of environmental factors was measured with generalized linear models for a binomial response (logit link function), where the dependent variable was arranged as the number of times selected cell i burned, b_i, and b_i minus the total number of fires simulated, N. The models of $\mathrm{BP_{var}}$, which was defined as the relative difference in BP (absolute values) from the $\mathrm{BP_{mean}}$ of each scenario, were structured like those for $\mathrm{BP_{mean}}$, but modeled a Gaussian response (identity link function). The natural log of $\mathrm{BP_{var}}$ values was used because of asymmetry in the data distribution, as well as in model residuals.

Two performance measures were used to evaluate relative contribution of each predictor variable. The first consisted of an adjusted R^2 computed for regression models using maximum likelihood estimates (Nagelkerke 1991), which could be interpreted as "explained variation". The second was the Akaike Information Criterion (AIC), a measure of goodness of fit in which models are penalized for each free parameter. Reported here was the change in AIC (ΔAIC) between reduced models (those omitting the variable of interest) and the full models. The importance of model terms is proportional to their relative ΔAIC values. Here, the predictor variables or interactions that resulted in a model with $\Delta\mathrm{AIC} < 4$ were considered poor predictors of BP (Burnham and Anderson 1998). Because some autocorrelation remained in the model residuals, it was necessary to adjust the ΔAIC according to the effective sample size (Dutilleul 1993). Very conservative sample sizes of 25 and 81 points were deemed suitable for the BP_{mean} and BP_{var} models, respectively, by identifying the number of data points corresponding to the spacing dictated by the start of a sill in the semivariograms of model residuals.

Local examination of BP patterns

BP within and surrounding ignition and fuel features were examined for selected combinations of factors and levels in order to adequately describe the fine-scale spatial patterns in BP. BP "profiles" were created by sampling BP values at every cell spanning a north–south transect at the center of the study landscape for selected scenarios in each of the three experiments (Fig. 2) and plotting them as a function of location (i.e., northness). In the ignitions experiment, BP was sampled across an area containing a high-density cluster feature (IGNIT = CluHi) for two levels of DIR (S and Rnd). In the fuels experiment, BP was sampled across an area containing a rectangular feature of slow fuels in a fast fuel matrix and one of fast fuels in a slow matrix (FUELS = Rec25 and Rec75, respectively) for scenarios using small and large fires (SIZE = Sm and Lg, respectively). In the weather experiment, the BP values of the three fire size distributions (DIST = Cst, Reg, and Exp) were sampled across the Rec25 FUELS feature with fires burning from random directions (DIR = Rnd).

Results

Effects of combinations of inputs on BP_{mean} and BP_{var}

In the ignitions experiment, BP varied mainly as a function of the ignitability ratio between ignition features and the surrounding matrix (Fig. 3a). Scenarios with high-density ignition features (CluHi and LinHi) had higher $NBPD_{mean}$ and $NBPD_{std}$ than scenarios with low-density features (CluLo and LinLo). Given a constant number of ignitions and uniform fuels, all scenarios of the ignitions experiment should have a $NBPD_{mean}$ of zero (Fig. 3a). That this was not always borne out is a result of proportionally more ignition features covering the study landscape than the buffer area, especially with clustered ignitions, for which there were no ignition features at all in the buffers. This caused an imbalance in the effective number of ignitions between the study landscape and its buffer, thereby creating an "indirect" edge effect. The DIR and SIZE factors mainly influenced $NBPD_{std}$. Southerly burning fires generally yielded greater variability than fires burning in random directions (Rnd), whereas small fires yielded greater variability than large ones. The $NBPD_{mean}$ within the ignition features (Fig. 3a, crosses) were always much less than the 10- or 2-fold ignitability differential between the features and the surrounding matrix.

In the fuels experiment, the $NBPD_{mean}$ and $NBPD_{std}$ varied mainly as a function of the overall flammability of the landscape, but apparent interactions with ignition patterns produced rather erratic patterns in BP (Fig. 3b). The inclusion of both spatially variable fuels and ignitions dramatically increased the $NBPD_{std}$, especially for the scenarios with clustered high-density ignitions. The $NBPD_{mean}$ within the fuel features (Fig. 3b, x's) differed substantially from overall $NBPD_{mean}$, but the relative difference was moderated when the ignitions patterns were nonrandom.

In the weather experiment, $NBPD_{mean}$ and $NBPD_{std}$ varied slightly with the DIST factor (Fig. 3c): the departure in $NBPD_{mean}$ decreased as fire size distribution became more variable. The DIR factor affected $NBPD_{std}$, with fires burning in westerly and random directions resulting in the highest and lowest $NBPD_{std}$, respectively. The overall and within-feature $NBPD_{mean}$ in scenarios using rectangular slow fuel features (FUELS = Rec25) was slightly lower for simulations with southerly winds than for those with westerly winds because the less flammable features were wider relative to the frontal fire spread of southerly winds. That the rectangular slow fuel features were more effective than round ones when the wind direction was random is somewhat surprising and suggests that this feature yielded a disproportionate reduction in fire size when it was oriented perpendicular to fire spread. The east–west alignment of fuel features (Fig. 2) resulted in small discrepancies in $NBPD_{mean}$ for circular fuels between southerly and westerly wind directions (Fig. 3c).

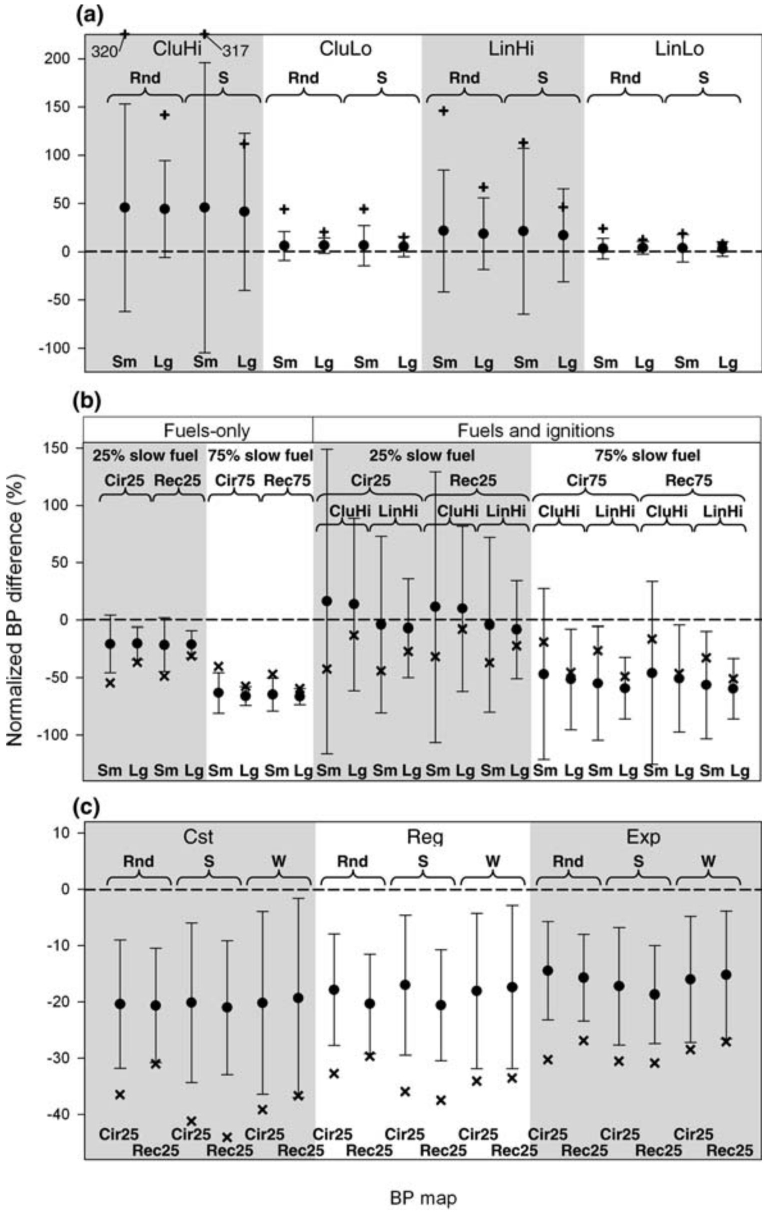

Fig. 3 Relative difference of burn probability (BP) values for scenarios using variable local inputs compared with scenarios using uniform local inputs in the ignitions, fuels, and weather experiments. Data are presented as means (*filled circles*) and standard deviations (*whiskers*). The *dashed line* at zero in each graph represents BP under uniform local conditions. By way of comparison, the mean BP within the spatial fuel and ignition features are shown as *crosses* and x's, respectively. **a** Ignitions experiment. The IGNIT factors (clustered high density [CluHi], clustered low density [CluLo], linear high density [LinHi], and linear low density [LinLo]) were plotted by the random (Rnd) and south (S) DIR factors and by the small (Sm) and large (Lg) SIZE factors. **b** Fuels experiment. The FUELS factors (circular features with 25% slow fuel [Cir25], rectangular features with 25% slow fuel [Rec25], circular features with 75% slow fuel [Cir75], and rectangular features with 75% slow fuel [Rec75]) were plotted by the clustered high density (CluHi) and linear high density (LinHi) IGNIT factors and by the small (Sm) and large (Lg) SIZE factors. **c** Weather experiment. The DIST factors (constant [Cst], regular [Reg], and negative exponential [Exp] fire size distribution) were plotted by the random (Rnd), south (S), and west (W) DIR factors and by the circular (Cir) and rectangular (Rec) features with 25% slow fuel FUELS factors

Relative importance of environmental factors

There was considerable variation in the relative contributions of the environmental factors among experiments, as well as between the BP_{mean} and BP_{var} models (Table 3). Both model types had fair to excellent explanatory power ($0.429 < R^2 < 0.944$), but the BP_{mean} models had higher R^2 values than their BP_{var} counterparts. As expected, BP_{mean} was influenced mainly by the weather-related factors SIZE and DIST, whereas BP_{var} was mainly a function of the IGNIT and FUELS factors. There was strong agreement between the two measures of variable importance.

In the ignitions experiment, SIZE explained almost all (97.4%) of the model variation for BP_{mean}. The small contribution of the IGNIT factor (2.4%) was due to the imbalance in ignitions between the study landscape and its buffer for the clustered and linear IGNIT inputs. Although the importance of SIZE dwarfed that of other factors, the ΔAIC suggests that all model terms but one (IGNIT × DIR) improved the BP_{mean} model. The IGNIT factor explained almost all of the variation in the BP_{var} model, with SIZE and DIR contributing minimally. According to ΔAIC, the interaction terms including IGNIT marginally improved model fit, whereas DIR × SIZE did not.

In the fuels experiment, the SIZE and FUELS factors explained most of the variation in BP_{mean}, but ΔAIC values suggest that all factors and interactions improved the model. Both the IGNIT and FUELS factors and, to a lesser extent, SIZE made strong contributions to the BP_{var} model. In addition, this model had a highly-significant contribution from the interaction term between FUELS and IGNIT, as

Table 3 Partitioning of variation (R^2) and change in model AIC for mean and variability of burn probability (BP) between groups of factors in each experiment

	BP mean		BP variability	
	% Variation explained[a]	ΔAIC[b]	% Variation explained	ΔAIC
Ignitions experiment				
R^2	0.830	–	0.636	–
IGNIT	2.4	15,529	94.9	1,586
SIZE	97.4	620,279	3.3	93
DIR	0.1	1,294	1.6	48
IGNIT × SIZE	0.004	24	0.1	4
IGNIT × DIR	0.0004	3	0.2	4
DIR × SIZE	0.09	557	0.004	0
Fuels experiment				
R^2	0.670	–	0.524	–
FUELS	24.4	229,494	15.9	888
IGNIT	2.3	21,999	54.2	1,525
SIZE	73.3	688,520	4.3	150
FUELS × IGNIT	0.01	94	24.1	571
FUELS × SIZE	0.04	362	0.2	6
IGNIT × SIZE	0.005	45	1.3	33
Weather experiment				
R^2	0.764	–	0.429	–
DIST	77.2	44,529	1.8	46
DIR	3.4	2,055	1.8	37
FUELS	19.0	11,094	94.5	1,136
DIST × DIR	0.04	24	0.08	1
DIST × FUELS	0.2	125	1.2	18
DIR × FUELS	0.1	57	0.6	9

Both measures compare the performance of the models in which the variable of interest is omitted to the model consisting of all variables

SIZE, fire size; DIST, fire size distribution; DIR, wind direction; IGNIT, spatial pattern and density of ignitions; FUELS, configuration and composition of fuels

[a] R^2 values are not reported as percentages

[b] The reduction in AIC from the full model when the factor of interest is omitted, adjusted for the effective sample size (see "Methods")

exemplified in the following section, and a moderate interaction between IGNIT and SIZE.

In the weather experiment, the DIST and FUELS factors contributed most to the explained variation in the BP_{mean} model. The DIR factor was also more important here than in the ignitions experiment because some combinations of DIR and FUELS had noticeable effects on BP (e.g., south-burning fires and rectangular fuel features). All interactions improved the model according to the ΔAIC values. The FUELS factor made by far the largest contribution to the BP_{var} model, but all other terms except DIST × DIR contributed to the model of spatial BP patterns.

Local examination of BP patterns

The BP profiles illustrate fine-scale patterns that may have appeared unimportant in the previous landscape-scale analyses (Fig. 4). For example, the DIR factor was the least important at the landscape scale (Table 3) but strongly modified BP patterns in and around areas of clustered high-density ignitions (CluHi) (Fig. 4a). Fires burning exclusively from the south generated a strong positive "fire shadow" on the lee side of the ignition feature, whereas random wind directions produced a less concentrated but much larger-ranging shadow around the ignition feature.

The BP profiles from the selected fuels experiment scenarios indicate a complex relationship between the duration of fire-conducive weather (SIZE) and fuel patterns. The high- (Rec25) and low-flammability (Rec75) levels of the FUELS factor yielded seemingly reciprocal patterns, but they were not perfect mirror images (Fig. 4b). Although large fires produced much large BP shadows than small fires, the relative contrasts in BP patterns produced in fuels of opposite flammability appeared to be far greater with small fires than with large ones.

The three levels of the DIST factor produced similar forms of BP shadows in and around a rectangular fuel feature (Rec25) (Fig. 4c). However, the absolute BP values varied substantially among levels, despite burning for the same period of time, on average. In fact, the lowest BP values of the Rnd DIST level (those in the center of the fuel feature) were higher than the highest BP of the Cst level. In addition, these results show that high variability in the duration of fire-conducive weather (DIST = Exp) produced only about a 25% reduction in BP within the fuel feature compared to a 40% reduction for the low variability level (Cst) (Fig. 4c).

Some combinations of simple and easily interpretable inputs produced unanticipated BP patterns, such as the scenario using the Cir25 and LinHi levels of the FUELS and IGNIT factors, respectively, with southerly fires and both Sm and Lg levels of the SIZE factors (Fig. 5). When fires were small, the slow fuel features were always effective at reducing BP, even when these coincided with ignition features (Fig. 5a). This was true even for the central fuel feature, which experienced the highest concentration of ignitions

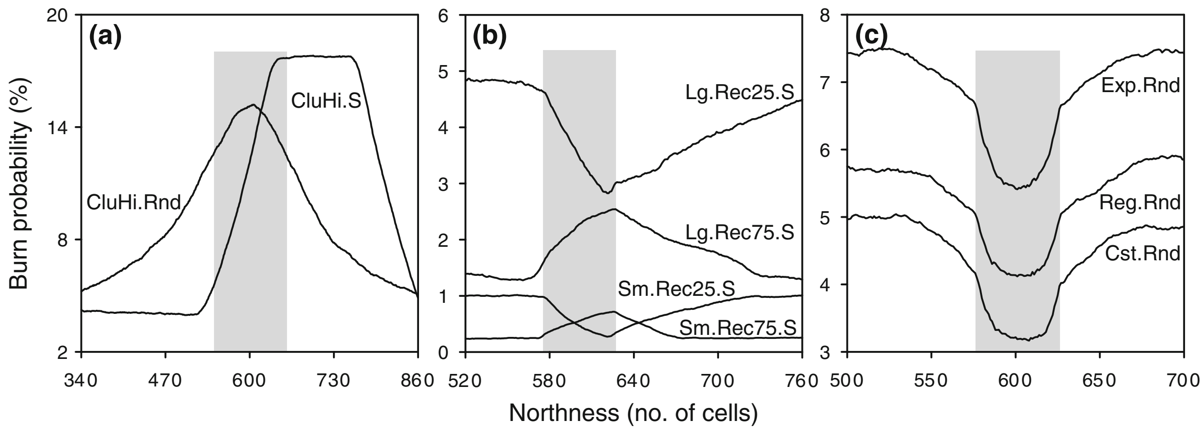

Fig. 4 Burn probability across a north–south transect (see Fig. 2) through the center of the landscape for selected scenarios from the **a** ignitions, **b** fuels, and **c** weather experiments. Abbreviations for the factor levels as defined in Table 1. *Shaded areas* represent the area covered by the fuel or ignition feature

because of the two intersecting linear ignition features. However, the within-feature BP reduction, as well as the leeward effect on BP patterns varied according to the position and level of overlap between fuel and ignition features (Fig. 5b, c).

Interactions between fuel and ignition patterns were amplified when the simulated fires were large. Notably, the efficacy of fuel features at reducing BP was highly variable throughout the landscape (Fig. 5d). At one extreme, high BP values resulting from the confluence of the two linear ignition features overwhelmed any mitigating effect of the central fuel feature, whereas fuel features on the leeward side of ignition features appeared to produce a large BP shadow (Fig. 5e). The overlay of fuel and ignition features lead to the creation of an intriguing lenticular pattern in BP on the lee side of the fuel features (Fig. 5f). This pattern can be explained by the combined effects of fires successfully spreading through and beyond the fuel feature and fires flanking from the right side of the feature. The relative decrease in BP to the left of this pattern is a result of fewer ignitions, because of the diagonality of the ignition feature and the greater time traveled by fires ignited at the southernmost part of the fuel feature, which significantly reduced frontal fire spread.

Discussion

Our results show that a limited set of simplistic ignitions, fuels, and weather inputs can yield complex responses in the mean and spatial patterning of BP. The model output were usually consistent with our understanding of controls on BP (Fig. 1), but this was not always the case, affirming that fire regimes are a manifestation of highly-intertwined and complex relationships among a set of environmental drivers (Peterson 2002). Furthermore, although weather-related factors had a greater effect on mean BP, and ignition and fuels chiefly influenced BP variability, our results did not fully support the assertion that environmental factors could be cleanly partitioned into ‘top-down’ and ‘bottom-up’ controls on these two BP measurements.

Characterizing a control on BP as either top-down or bottom-up is problematic. For example, weather-induced temporal synchrony of fire events over large areas clearly exerts a top-down influence (McKenzie et al. 2006; Gavin et al. 2006), but the extent to which fuels amplify or mute the impact of weather may be difficult to assess. Similarly, the dependence of ignitions on weather for ignition sources (lightning) and suitable dryness of the fuelbed suggests that

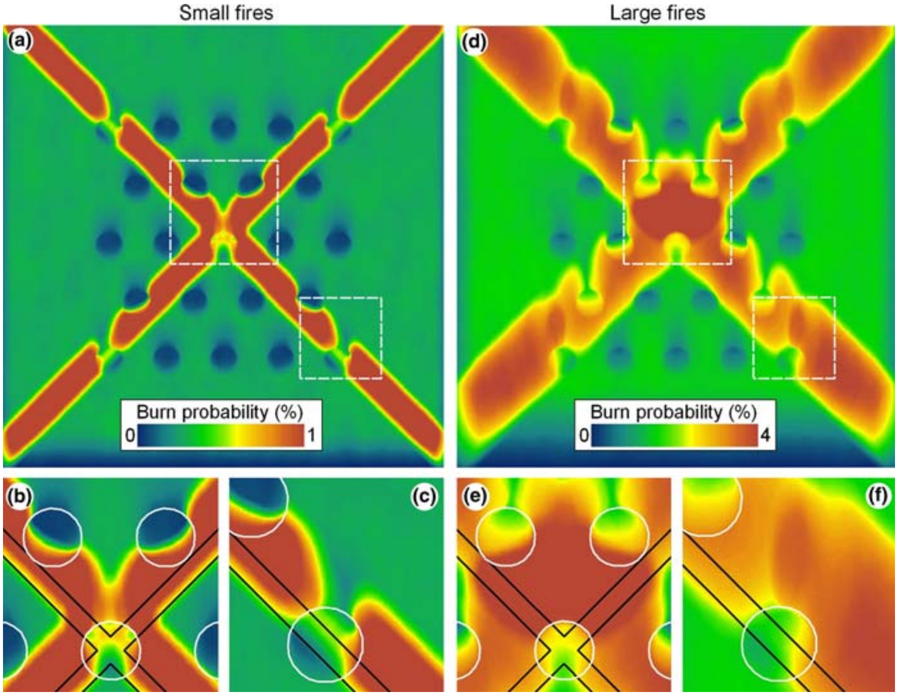

Fig. 5 Interaction of fuel and ignition features on burn probability (BP) patterns. **a** Map produced by simulating small fires on a landscape of circular features of slow fuel (Cir25), linear high-density ignitions (LinHi), and winds blowing from the south. The 250-cell buffer area is also shown. **b**, **c** Close-ups of the BP map. **d** Map produced by simulating large fires; again, the 250-cell buffer area is shown. **e**, **f** Close-ups of the BP map. The edges of the fuel and ignition features are shown as *white* and *black* lines, respectively

ignitions obscure the top-down–bottom-up categorization; lightning-caused ignitions may appear to be more top-down, whereas distinct patterns of human-caused ignitions may be considered more—but not entirely—bottom-up.

This study highlights the complex role played by ignitions in defining fire likelihood. Simple interactions with other environmental factors may considerably affect the spatial patterns in BP in and around an ignition feature. For example, our results show that varying the constancy of wind direction and the mean duration of fire-conducive weather (fire size) may not alter the overall likelihood of fire, but effectively modulate a tradeoff between the relative BP contrast (i.e., between high- and low-BP areas) and its spatial dispersion (extent). This has practical implications for wildfire-risk analysis in which fire likelihood is estimate from a single set of mean or median conditions, including a single wind direction. However, in areas where large fires predominate, as in boreal biomes, and wind direction is fairly constant, the impact of ignition location on BP patterns is strongly diluted (Barclay et al. 2006).

As with ignitions, the results of a few simplistic manipulations of fuels—which have long been considered the most "controllable" aspect of fire risk—hint at its multi-faceted relationships with other factors. Our results are consistent with those of Finney (2001), who reported a nonlinear response of area burned to the ratio of fuel treatment (i.e., feature) and fire size for individual fires. This phenomenon was observed here as a reduced fuel treatment effect on BP when fires were relatively large (Fig. 4). This is due to the nonlinear (power function) increase in area burned according to the rate of spread. Interpreting BP patterns resulting from varying mean fire sizes and fuel configurations is thus not straightforward. For example, a fuel patch with a rate of spread that is half that of the matrix, which represents a substantial discrepancy in real landscapes, may do little to reduce landscape BP if the fire size is large compared to the patch size.

Given its overarching influence on the fire environment, it is difficult—and perhaps even impossible—to discuss the role of weather without implicitly considering fuels and ignitions. As such, the characterization of fire regimes as weather- or fuels-dominated seems overly categorical. There are fire-prone systems where weather is the dominant cross-scale factor affecting fire likelihood, such as the shrublands of some Mediterranean climate areas (Moritz 2003; Nunes et al. 2005). However, these systems represent an extreme in fuels homogeneity (from a fire spread standpoint) and fire weather severity; fuel and fire weather conditions are more variable in most fire-prone systems (Keane et al. 2009). Nevertheless, our results suggest that large weather-driven fire events exert a disproportionate influence on BP patterns and are consistent with the idea that very large fires periodically homogenize landscapes (in terms of age class distribution) and diminish the influence of fuels on BP (Baker 1994; Kerby et al. 2007).

The peculiar localized spatial patterns seen in our results exemplify how emergent properties result from a set of simple inputs. The interaction between ignition density and the relative flammability of fuels can create an array of BP patterns by compensation or competing effects on fire spread. On the one extreme, when two linear ignition features intersected, an area of disproportionately high BP (a "fire concourse") created conditions largely overwhelmed the potential effect of the slow fuel feature. By contrast, under certain environmental conditions (e.g., small mean fire size) and a particular placement, the 10-fold increase of the ignition features was largely muffled by the same fuel features. This phenomenon is relevant to the placement and configuration of fuel treatments. Although fuel treatments are often effective at limiting the rate of spread (and hence the size) of large wildfires, their perceived benefits could be reduced if the number of ignitions increase (LaCroix et al. 2006) because of, for example, increased road access (Syphard et al. 2007).

The use of heuristic artificial landscapes, rather than stochastically derived neutral or fractal landscapes, allowed us to refine our understanding of the relative contribution of each factor because the resulting BP patterns could be attributed to one or more causal factors. Although this approach offers tremendous opportunity to learn, the current computational demand for models such as Burn-P3 poses a challenge to the use of a very large factorial design (e.g., Clark et al. 2008), or inter-model comparisons (e.g., Cary et al. 2006). Furthermore, because vegetation succession was not addressed, it was not possible to evaluate potential feedbacks over a temporal horizon. Rather, the strength of the Burn-P3 model is rooted in the accuracy of fire spread. A highly-accurate fire spread module further enhanced our ability to detect very subtle changes in BP. Furthermore, an accurate depiction of emergent spatial fire patterns is essential to our understanding of, and ability to predict, key ecological interactions, such as landscape-scale changes in species composition (Wimberly 2004).

Conclusions

The potential challenge of isolating the effects of the environmental factors that control patterns in BP were partly overcome by studying a set of simplistic artificial landscapes. The results reaffirm the importance of explicitly modeling fire spread in order to account for topological dependencies on the landscape. In many of the simulation scenarios, neighborhood effects coupled with interactions among a small number input variables generated unpredictable outcomes that, despite the simplistic inputs, required further examination of the BP patterns in order to be fully understood. These results reinforce the claims that injecting variability into simple controls of fire-prone systems results in significantly altered fire patterns (Lertzman et al. 1998). Although it was useful to separate fire susceptibility into its mean and variability components—something that appears to be a source of confusion and debate in the fire patterns literature—our results suggest that, in light of natural complexity, it would be extremely difficult to successfully partition the relative contribution of environmental factors in real landscapes. Rather, a more realistic goal may be to describe the manner in which the combinations of factors generate landscape fire patterns.

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